A Robotic System for Steel Bridge Maintenance: Field Testing

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Abstract

This paper presents the field testing results of an autonomous manipulator-based robotic system that strips the paint and rust from steel bridges [Liu *et al.*, 2008]. The key components of this system are sensing and planning, which have been presented in other research papers. The grit-blasting field trial presented in this paper spanned 6 weeks, and included 20 hours over 4.5 days of actual grit-blasting operation. The field testing has verified the algorithms developed for exploration, mapping, surface segmentation, robot motion planning and collision avoidance. It has also proved that the robotic system is able to perform bridge maintenance operations (grit-blasting), reduce human workers' exposure to hazardous and dangerous debris (containing rust, lead-based paint particles), and relieve workers from labour-intensive tasks. The system has been shown to position a grit-blast nozzle so as to remove the paint and rust at the same rate that is expected of a worker with equivalent equipment: small grit-blasting pot and medium-sized hose nozzle. Testing in the field has also highlighted important issues that need to be addressed.

1 Introduction

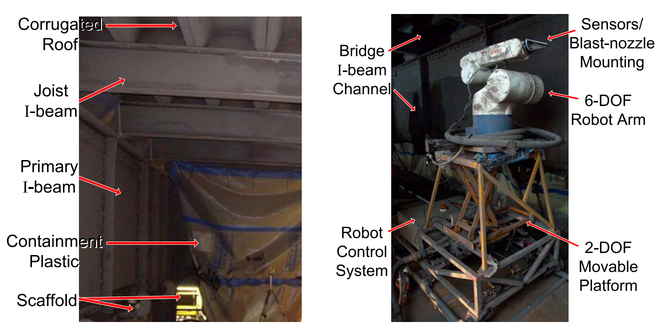
Paint and rust removal, by means of grit-blasting, followed by the reapplication of a protective coating is an essential operation of steel bridge maintenance. The presence of asbestos and/or lead-based paint and silicosis-causing grit [Lahiri *et al.*, 2005] results in a potentially hazardous environment [Kirchner *et al.*, 2006]. The grit-blasting operation itself is extremely physically demanding since the equipment used in grit-blasting is often heavy and is subject to large reaction forces due to the recoil from the blast nozzle [Joode *et al.*, 2004]. Hence, the assistance of an autonomous robotic system has the potential to greatly increase productivity and to reduce the workers' exposure to risk.

Recently, there has been increasing research interest in the use of robotics technology for in situ maintenance of steel structures such as ships, steel bridges, storage tanks, etc. Several prototype systems have been developed and field-tested including a Robotic Bridge Maintenance System [Lorenc *et al.*, 2000]; HydroCat [Echt *et al.*, 2000] for removing coatings from structures in marine and non-marine industries; Hull Jet [Echt *et al.*, 2000] for large ships, barges, floating dry docks and vessels; a large robotic paint stripping system for aircraft maintenance [Schmitz, 2003]; and a teleoperated robotic bridge maintenance system [Moon and Bernold, 1997] capable of remote inspection, spray washing, paint removal and painting. The capabilities of remotely operated robotic systems critically depend on a skilled operator's decisions when controlling the robot movements.

In order to apply an autonomous robotic system for bridge maintenance operations in an initially unknown complex 3D environment, many research challenges and development challenges need to be addressed [Liu *et al.*, 2008]. A detailed 3D map of the surface geometry is required. Although a complete CAD model would be ideal, it is too laborious to generate this even for a skilled practitioner. Therefore, a map of the surface geometry must be generated through sensing. The map must then be used to plan safe and efficient trajectory grit-blasting paths, and the corresponding motions for the manipulator. Therefore, it is vital that the system has the technologies and the enabling methodologies to sense the environment and to plan motions.

An autonomous exploration and mapping solution is desirable since it can improve the productivity and safety of the system. Methods of exploratory sensing and mapping exist for mobile robotics and mobile manipulators [Thrun *et al.*, 2004][Garrido *et al.*, 2008][Rusu *et al.*, 2008][Paul *et al.*, 2009]. The lightweight Hokuyo URG-04LX laser range finder presented in [Kawata *et al.*, 2005] has been shown to enable surface material-type identification in some specific applications through the Laser Range Classifier (LRC) [Kirchner *et al.*, 2007]. A system for Autonomous eXploration to Build A Map (AXBAM) was developed [Paul *et al.*, 2007b][Paul *et al.*, 2009] to explore and build a geometric map of an environment, using efficient and collision-free manipulator path/motion plans [Webb, 2008]. Surface data fusion [Curless and Levoy, 1996], which is required during sensing, has been extended by [Webb, 2008] into a real-time implementation that can handle both thin plates and sharp features.

Another important capability, which an autonomous mobile manipulator system requires, is the ability to plan the movements of the robot to perform tasks in relation to the map. Algorithms have been developed that generate blasting target points [Paul *et al.*, 2007a], optimised manipulator poses [Webb, 2008], and optimised trajectory plans [To *et al.*, 2009] for selected surfaces, which can then be executed safely. Coverage modelling [To *et al.*, 2009] can be performed on these plans to predict the outcome of a painting or grit-blasting task. A mobile manipulator system can thus sense an environment and perform the required planning on the generated map to allow a task, such as grit-blasting, to be performed.



(a) (b)

Figure 1: *a)* One side of an I-beam channel with three sections requiring grit-blast maintenance. *b)* Grit-blasting system: a 6DOF manipulator on a 2DOF base.

An autonomous manipulator-based robotic system has been developed (Fig. 1*b*) which was first presented in its early stages in [Liu *et al.*, 2008]. The developed system now contains the components for sensing the surrounding environment, and planning/ executing grit-blasting operations in a complex 3D environment. This paper presents an overview of the mobile manipulator robotic system. The system is verified through an extensive field test in the target steel bridge maintenance environment shown in Fig. 1*a*. The experiments are used to verify the devised algorithms for 3D map building, collision avoidance, planning and manipulator control, along with the developed sensor package and mobile platform. Based on the field testing results many observations are made regarding the challenges of working on-site in a real-world environment compared with working in the laboratory.

The breakdown of this paper is as follows: Section 2 describes a brief overview of the system. Section 3 confirms the system capabilities through field-testing results. The limitations are also identified in Section 3 along with numerous on-site challenges, and this leads to a discussion of the key outcomes and the ongoing research and development. Finally, Section 4 presents the conclusions and the future work.

2 System Overview

The proposed robotic system (Fig. 1*b*) consists of a 6-DOF industrial robot, a vertical lift, a controllable platform which can move laterally along a set of rails, a sensor package including a laser range scanner and a camera, and a high performance computer. The prototype development involves the integration of all functional components (e.g. sensing, map building, planning, control etc.) on the hardware, and the integration of the autonomous system with grit-blasting equipment.

There are many research and development issues that have been overcome in order to develop this system. Prior to relocating into the field, this system performed successful sensing, planning and execution in a laboratory environment which contains general structural members with slightly different dimensions. The key research issues for a system working in an initially unknown field environment relate to the sensing of the environment, and the subsequent task objectives-based path and motion planning of the actuator, in this case an industrial robot manipulator. In terms of development, the platform and vertical lift have all been predominantly developed in-house, while the hose, nozzle and cables have been provided.

Fig. 2 shows the system process diagram where the environment is sensed at discrete base positions calculated by the system, and then the map is used to autonomously plan: a blasting path, the corresponding manipulator poses, and the safe manipulator trajectories between poses.

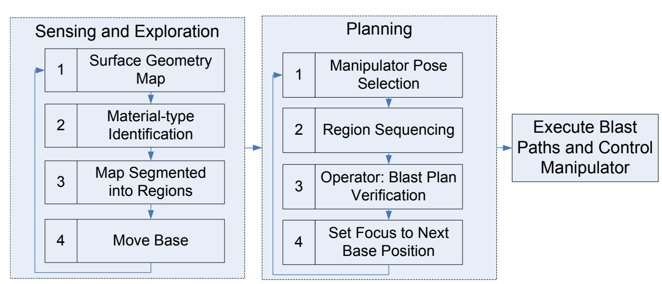


Figure 2: Process diagram of the grit-blasting mobile manipulator system

2.1 Sensing and Exploration

The focus of sensing is twofold: to acquire the geometry of surfaces in the environment, and to perform surface-type identification. An approach has been developed [Paul *et al.*, 2009] where the manipulator is manoeuvred through a sequence of viewpoints that are selected to maximise the quality of the map generated, minimise the time taken for the exploration, as well as minimise the uncertainty of the surface-type estimation, all whilst avoiding potential collisions between the manipulator and the environment. Information theory is used to measure the information remaining in a map. Ellipsoidal virtual fields are positioned around the manipulator's links so that distance queries can be performed and collisions with obstacles in the environment are avoided. Surface-type identification is made possible through intensity measurements, which indicate the reflectivity of the surface when illuminated by an infra-red laser. The collected sensor data is fused into a map and known models from the environment are manually fitted so as to complete the map (i.e. remove holes and correct the surfaces in the corners).

2.2 Planning

The second stage of the system is planning the surface blasting. The planning approach [Webb, 2008] can be divided into six phases. (1) Assign each bridge section to the platform location where it will be blasted. (2) Partition surface points into six orientation classes, using a coordinate frame aligned with the I-beam, and the geometric work cell based on the position of the surface point relative to the coordinate frame at the manipulator base. (3) Select a coverage path pattern for each patch from four possible variations of a boustrophedon pattern, which are evaluated by planning manipulator joint space trajectories over each. A pattern is selected based upon the manipulator motion, and the number of turn points. (4) Manipulator joint configurations are found, which move the blast spot along the surface path, by applying the Levenberg-Marquardt (LM) algorithm to minimise a cost function that includes blast stream length, blast stream angle to surface, manipulator's proximity to obstacles, and joint state limits. (5) A genetic algorithm [Ponnambalam *et al.*, 2004] is applied to this travelling salesman problem (i.e. surface patches are cities and the maximum manipulator joint motion is used for the distance) to select the sequence that surface patches are treated. (6) Safe patch-to-patch motions are sought to avoid the need to stop the high pressure air when transitioning between surface patches. A safe motion requires the grit blast stream to always be directed at a metallic surface. A modified bi-directional rapidly exploring random tree (RRT), which utilises the LM algorithm, is applied to this part of the planning.

3 Field Testing Results

The field testing is conducted in an I-beam channel underneath a large steel bridge as shown in Fig. 3. The general sensing and planning algorithms, which can handle structured environments with various geometries, are applied to the target area. The target area is the roof and one side of the $13m$ length I-beam channel. The I-beam channel consists of two parallel I-beams, which run lengthwise (i.e. parallel to the traffic flow) along the steel bridge, and horizontal joist I-beams which run perpendicular to the primary I-beams. Scaffolding is already erected underneath the I-beam channel. The target area is completely enclosed in plastic containment material. Extraction fans are used during grit-blasting to negatively pressure the environment, which prevents contaminated refuse from escaping the containment. The blasting equipment that was provided includes a small-sized hopper (i.e blasting pot) which is filled with approximately 20kg of garnet at a time. The nozzle used is a medium-sized venturi nozzle with a bore-hole diameter of 10mm. The field testing exercise took place over

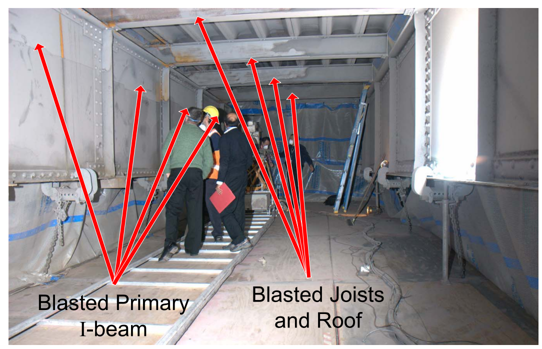


Figure 3: I-beam channel one week after blasting the roof and upper left side of the primary I-beam. Notice that surface rust has already begun to appear.

approximately 6 weeks, and is roughly divided into six main phases: Setup Environment, Environment Sensing, Blast: Simulate & Tune, Platform Engineering, and Actual Blasting. In the Setup Environment phase, the system and supporting equipment are transported from the laboratory to the bridge and installed. However, the current system is not yet designed with a focus on portability; hence, the setup phase is a laborious process. Once the system is installed and setup, the Environment Sensing phase can commence. This phase focuses on exploring and mapping the area numerous times, and calibrating the movement of the mobile platform and the sensors. The resulting maps are studied closely for flaws and Map Improvement is used to optimise the maps so they are complete and smooth enough to be used for the planning process. Currently, this map improvement stage is done manually. A map that has been verified can then be used in the Blast: Simulate & Tune phase. In this phase, manipulator motions are planned based upon the map, and the grit-blasting parameters (e.g. blasting patterns/ speed, and effective nozzle-to-surface distance) are fine-tuned. During field testing many Platform Engineering tasks had to be completed including: manufacturing modifications to the rails; engineering the motors and brakes of the platform; and managing the signal cabling, power cabling and the hose. Finally, the Actual Blasting can commence, such that the planned paths are executed with actual grit being passed at high-speed through the nozzle. The results of sensing and grit-blasting are presented henceforth.

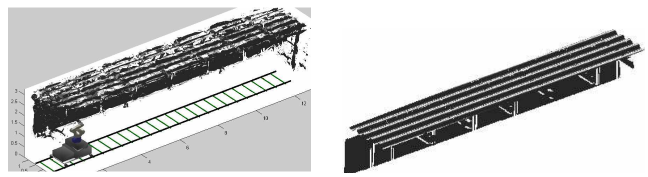
3.1 Exploration and 3D Map Generation

Generating a map of one-side of the 13 meter-long channel can be completed over approximately 3 days as detailed in Table 1. This process combines wheel encoder data, the robot manipulator joint angle data, and the laser range data to generate maps.

Table 1: 3D Map Generation Results

Identifier	**Result**
Range grid files collected	500
Average points per range grid file	70000
Total time scanning: robot lowered	5 hours
Total time scanning: robot raised	5 hours
Average time to get 1 range grid file	60 sec
Approximate map improvement time	2 hours
Total triangles prior to improvement	1.68×10^6
Total triangles after improvement	0.78×10^6

The period of 5 hours to generate a map may appear to be overly time consuming. It is in fact possible to generate a reasonable map of the surface geometry in under 10 minutes based upon a single scan every 2 meters along the platform. However, on closer inspection the quick map has many deficiencies: there are many holes in what should be continuous surfaces; there are spurious surfaces; occlusions; missing corners; and low resolution portions. It was not possible to improve the quick map to a required state using hole filling algorithms and manual map augmentation. A map with the listed deficiencies cannot be used to plan the complete blasting motion over the surfaces. This is because a hole in the map must be avoided during planning, which adds significant complexity to the planning process when compared to planning over a complete and smooth surface. Holes in the sensor data occur frequently on the corrugated ceiling surfaces, where motion planning is already challenging due to the variation in surface normals. However, by performing exploration to determine the viewpoints needed to gather enough data to complete the surfaces, and then fitting functions to the data, the required quality map can be generated. After scanning between 30 and 50 times at each base location the maps improved significantly. At times, the collection of data was hampered by problems with the encoders, which required additional calibration. However, after multiple mapping runs and encoder calibration these problems were overcome and a relatively smooth, near-complete map was generated with 10mm-20mm accuracy as shown in Fig. $4a$ for more than $50m^2$ of surface area with a 10mm voxel resolution. Maps are improved as shown in Fig. $4b$ by optimisation and fusion of the map data collected, and the fitting of data to surface model functions.

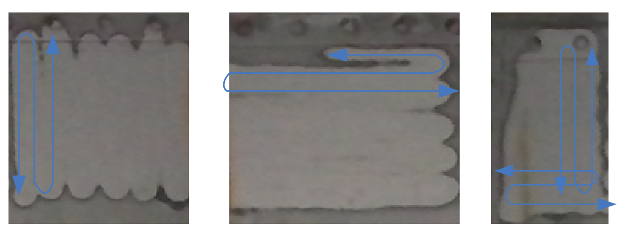


(a) (b)

Figure 4: *a)* Laser scanning sensor-based map of one side of 13m I-beam channel; *b)* After map improvement stage

3.2 Planning and Grit-blasting Results

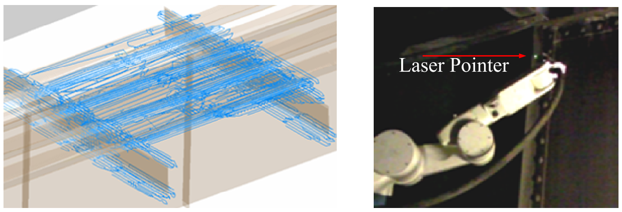
The results of the first grit-blasting experiment are shown in Fig. 5. This experiment was used to determine the blasting parameters, the orientation of the boustrophedon patterns for blasting (i.e. left-and-right, up-and-down or a combination of the two), and distance between tracks. There is minimal performance difference between blasting vertically (Fig. $5a$), horizontally (Fig. $5b$), or overlapping the two (Fig. $5c$), which uses twice the amount of grit and time.



(a) (b) (c)

Figure 5: Tuning blasting parameters. Patterns tested include: *a)* Up-and-down; *b)* Left-and-right; *b)* Combination of up-and-down and left-and-right.

Grit-blasting plans were determined as presented in the previous section. The output of the planning process is a set of joint angles, which correspond to the manipulator being directed at a desired area in the map. To ensure the safety and efficiency of the plans, computer simulations of the robot blasting movements were studied (Fig. 6*a*), and "dry runs" of blasting were performed with a laser pointer affixed to the nozzle (Fig. 6*b*).



(a) (b)

Figure 6: Prior to blasting, simulations and dry-run tests are performed to ensure the nozzle is not directed at incorrect areas and the motions are safe. *a)* The simulated environment showing the grit-blasting spot plan as it traverses the surfaces indicates the coverage and manipulator movement; *b)* The manipulator with a laser pointer affixed doing dry runs.

Once the dry-runs demonstrate the safety of the manipulator movements, the actual grit-blasting commences. Fig. 7 shows the grit-blasting of the primary I-beam as the planned paths are executing over the surfaces. Fig. 7*a* shows the manipulator position just after blasting commences. The dust is not initially significant and so the blasted area can be clearly seen. However, in Fig. 7*b* and especially in Fig. 7*c*, the dust makes it difficult to see the system and blasting results. This is despite the camera only being 3 meters away from the system, and a large dust extractor being used to remove the dust from the air. After blasting is complete, it takes several minutes for the dust in the air to settle, at which time it is possible for humans to enter the environment and inspect the results. The results are presented in Table 2 for one section out of the six that were attempted. Fig. 8 shows the section is on the left-hand side between two roof joist I-beams and the platform lift table is raised. One section is defined as the area between two joist I-beams (i.e. Fig. 7*a*).

Table 2: One Section Results

Identifier	**Result (Approx.)**
Area covered	$9m^2$
Robot position	$6.4m$ along track
Blasting time	227 minutes
Total time taken	300 minutes
Grit used	17 bags (170kgs)
Individual blast regions	200
Time to use 1 bag of grit	8 minutes
Estimated coverage	95%+

Blasting was performed with a medium ($10mm$) blast nozzle and small blasting pot. On average it took 17 minutes to empty a pot filled with 1.8 bags (18kgs) of grit. Based on the results, 1 pot was able to cover a surface area of approximately $1m^2$. The section took approximately a full work day to complete due to the overhead of manually handling the garnet and refilling the blasting pot.

The overall results for grit-blasting five sections out of the six sections in the I-beam channel are shown in Table 3.

Table 3: Overall Blasting Results

Identifier	**Result (Approx.)**
Area coverage	$45.59m^2$ (5 sections, on channel left-hand side)
Estimation of grit used	80 bags (800kgs)
Blasting time taken	12.5 hours
Estimated coverage	90%

All results are approximate and are calculated by analysing the videos of the process, comparing blasting plans with an operator's post-blasting inspections, and by analysing the recorded system log files. However, it is difficult to record both precise time measurements (due to limitations with the blasting pot often needing to be refilled) and precise measurements of blasting coverage.

The sixth section was not attempted since it was too close to the operator setup, and also due to time constraints. Table 3 shows the results gained with the provided equipment of a medium-sized nozzle and a small blasting pot. The main reason for the overall blasting completion average (90%) being less than the best section (95% from Table 2) was twofold.

Firstly, there were problems in two sections with garnet getting stuck in the blasting pot provided, which results in areas of ineffective blasting. There is currently no visual sensing feedback loop for in-process monitoring that could provide the system with the capability to sense the areas where coverage was poor.

Secondly, human error was a limiting factor. The blasting pot emptied approximately every 17 minutes, and there is no significant difference in air pressure (the only in-process autonomous system monitoring). Therefore, it is up to the operator to stop the robot and manually fill up the blasting pot. If the remote operator misses by a few seconds the audio cue signifying that there is no garnet left in the pot, then small areas are missed.

(a) (b) (c)

Figure 7: Actual grit-blasting stages from the blasting of the main I-beam on the left-hand side of the channel. Notice that as the blasting is completed the images become noisier. This is due to the airborne dust which results from the grit-blasting process. The images are in black and white to improve the image clarity.

(a) (b) (c)

Figure 8: Blasting one section with a total surface area of $\approx 9m^2$ with less than $0.1m^2$ missed. *a)* Results from blasting the primary I-beam web (i.e. "the wall"). The corners and the rivets are blasted including the vertical ribs and the underside of the top flange; *b)* Results from blasting the roof. The intended coverage is the first 3 corrugations. Only 3 small regions are not blasted to the required class; *c)* Results from blasting the joist I-beam. The robot can only reach the I-beam around the first 3 roof corrugations.

3.3 Issues identified

Throughout the field testing there were many research and development issues identified. The development issues were as follows:

- **Safety system:** the blasting pot is still controlled by the remote operator, even though the operator cannot reliably see the state of the system either with CCD cameras or by directly viewing.
- **Rails:** the manufactured rails were cumbersome and difficult to transport/setup on-site.
- **Platform positioning:** encoders gave false readings because of the significant vibrations on the bridge due to traffic.
- **Vertical lift:** was needed to reach the roof, however the mechanism is still manually adjusted.
- **Cable management:** since 3-phase power, 240V, high-pressure air, and data lines are all required, safe on-site cable management is challenging.
- **Hose management:** is challenging due to the complex manipulator movement during grit-blasting.
- **Air motors:** did not provide ideal control and accuracy of the platform position.
- **Brakes:** that maintain the platform position catch on the sleepers since design tolerances are not robust enough to allow for uneven scaffold surfaces.

The sensing issues were as follows:

- **Spurious laser data:** the data often varies more and has more incorrect readings than lab data.
- **Dust particles:** remain in the air for a long time, and cause false returns from the sensors.
- **Incomplete exploration:** the occupancy-based exploration approach may stop exploration prior to the triangular surface mesh being complete.
- **Incomplete maps:** cause planning problems so the research question is how to use inference and prior knowledge to improve the completeness of a map used for planning.

The planning issues were as follows:

- **Segmentation:** during planning the map must be segmented to maximise productivity and to minimise robot motion.
- **Blast pattern selection:** since there are many ways of covering a surface, even with the boustrophedon pattern, selecting the optimal pattern is still an unsolved issue.

- **Region sequencing:** after segmenting into regions it is challenging to determine the most productive order to blast the regions.
- **Heavily laden manipulator:** when a large nozzle was tested (results not presented here), the force on the end-effector increased by 30%, which increased the communication latency and resulted in executed motions not matching planned motions; this requires further investigation.

4 Discussion

The field testing results verify the prototype of the system. The system is the first of its kind capable of sensing and mapping a steel bridge environment, and then planning a suitable collision-free grit-blasting pathway. By assisting workers to do the difficult, hazardous and laborious grit-blasting task, the system is able to reduce the risk of injury, and reduce workers' exposure to large forces, fine dust/paint particles and the dangerous blast stream. Thus, there is a significant health, safety and economic impact. The system can be supervised and interacted with remotely by an operator who is kept outside of the containment area, and thus a safe distance away from the blasting operation.

Overall, the productivity of the actual grit-blasting was found to be equivalent to the continuous operation by one worker; the main limitation is currently the size of the blasting pot and the nozzle size. The average blasting rate was found to be approximately $4m^2$ per hour (for a medium-sized nozzle, air pressure between 80-100 psi, and small pot: 17 min pot). The robotic behaviour of the system (i.e. repeatable and continuous) generally provided acceptable quality control, and the planning process was able to be used for quantitative management (i.e. to measure and predict time, coverage, and grit usage). The system was able to reach areas that are difficult for human workers (corners, upper I-beam flange, ceiling), and to perform work on the primary I-beams and the roof without erecting the usually-required additional scaffolding.

The system still faces several research challenges which must be investigated. Due to the size and complexity of the environment, complete maps are difficult to attain. The exploration and map generation is a time consuming process which if included results in the system overall being less productive than a worker. Fused sensor data can be sufficient for manipulator collision avoidance and motion planning. However, additional sensing often does not generate maps of the required quality. Since the environment is essentially structural, research is required to seek techniques for improving the fidelity of the map of the environment based on map improvement processes that use inference and prior knowledge. Techniques are required to improve environment map segmentation, and to help select the optimal platform base position. For a given environment the ordering of segments is paramount in determining an efficient path in terms of time, distance of joint travel and grit usage. The region sequencing process along with the ideal base selection needs to be combined into a single optimisation problem to provide more intuitive automatic segmentation.

In complex operational environments such as in steel bridges, human operators frequently utilise deviations of the system's sound from a normal pattern to be alerted to potential faults. In grit-blasting it has been found that the sounds made by high-pressure air with and without grit are quite distinct, allowing the status of the grit flow to be assessed remotely or without line-of-sight to the tool. Given that dust in the environment often obscures vision, one in-process monitoring solution could be to classify the status of the system based on the sound.

Finally, the system needs a more sophisticated real-time monitoring HRI interface contained in a rugged robust hardware package. The system interface device is required for a non-technical operator, so they might interact with the system and confirm the movements of the machine, verify environment maps, and assist in post-operational inspection.

5 Conclusion

This paper demonstrated a mobile manipulator assistive robotic system performing a grit-blasting task, which was previously performed manually, on-site at a steel bridge. The system uses sensing to build a 3D map which was segmented into regions to be blasted. Path planning is used to generate collision-free manipulator motions inside the map which are then subsequently executed to perform the grit-blasting task. In total, the grit-blasting field trial of this system operated for a period of 4.5 days that included 20 hours of grit-blasting operations, where the only interruptions during the work day was to refill the grit-blasting pot with the grit required to remove the paint and rust. The machine has been shown to operate over extended periods of time, and is estimated to perform grit-blasting at a rate equivalent to the manual operations performed by a worker who is given the same nozzle and grit-blasting pot.

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